



WSN BASED THERMAL MODELING: A NEW INDOOR ENERGY EFFICIENT SOLUTION

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Abstract- In this paper, we proposed to use the Efficient Indoor Thermal Time Constant (EITTC) to characterize the indoor thermal response in old buildings. Accordingly, a low cost, energy-efficient, wide-applicable indoor thermal modeling solution is developed by combining Wireless Sensor Network (WSN) and Artificial Neural Network (ANN). Experiments on both prototype and building room showed consistent results that the combination of WSN and ANN can provide accurate indoor thermal models. A linear approximation of these models makes it possible to estimate the EITTC of building room. Statistical computations confirmed these estimations by showing a strong correlation between the model's predicted EITTC and measured data. Thus the indoor thermal response under different indoor/outdoor conditions can be characterized. Finally, a model based adaptive heating Start/Shut control method is proposed and tested, with which, direct energy saving is achieved.

Index terms: Wireless Sensors Network, Back-propagation Neural Network, Thermal Modeling, Linear Approximations, Effective Indoor Thermal Time Constant

I. INTRODUCTION

Energy consumption of residential and commercial facilities takes about 40% in Europe and USA. In China, residential urban energy consumption tripled between 1996 and 2008 [1]. As a matter of fact, the energy consumption varies between different types of buildings. For example, low energy efficient buildings (especially old buildings more than 30 years) consume from 300 to 400kWh/m²=year, while modern buildings consume approximately from 150 to 200kWh/m²=year [2]. The improvement of energy efficiency in low energy efficient buildings can bring considerable environmental and financial benefits.

A common fact of these low energy efficient buildings is this: most of them are badly isolated, thus, the building's dynamic thermal behavior in response to environment factors is very complex due to many existing nonlinear and time-varying heat transfer effects. Thus, it is difficult to characterize the indoor heating/cooling effects under different environmental conditions. The lack of understanding on the thermal effects inevitably leads to a squandered usage of energy. The traditional way to optimize the building's energy efficiency is to renovate the building with new construction material, which is often expensive and time-consuming. The purpose of this paper is to demonstrate that by establishing an accurate adaptive thermal model, the indoor thermal response can be characterized. Thus, the existing heating/cooling system's efficiency can be optimized.

Sensors and sensor networks are more and more used in building related research [3][4][5]. WSN has been recently used in monitoring Data-Centers and Nuclear Facility [6][7]. Wired sensor network has been applied for maintaining the occupant's comfort within a large multi-use building [8]. Halgamuge *et al.* further proposed method in optimizing the energy consumption of the WSN used in building monitoring[9] while Artificial Neural Network (ANN) has shown growing interests in thermal modeling of buildings [10][11].

Indeed, among most previous works on indoor thermal modeling, a limited number of sensors have been applied, mainly due to the fact that the data acquisition by wired sensors is usually expensive and time-consuming. These researches focused on macroscopic modeling of buildings, they consider large rooms as big thermal capacitors with homogeneous temperature. ANN used for thermal mapping of a cold storage is presented in [12], however, this model does not involve outdoor conditions, and it cannot provide in-time predictions of indoor temperatures.

The authors of this paper proposed methods of combining WSN and ANN in indoor thermal modeling [13]. We think there are two main advantages of applying WSN and ANN in building room thermal modeling. First, the nature of WSN and ANN makes them a perfect combination: on one hand, WSN could be easily and rapidly implemented, providing a huge quantity of sensor data. These data sources in return could be essential for the ANN to identify a fine grained thermal model. Secondly, they have high practical values: mathematical thermal modeling approaches [14] are usually used in general simulations. They are hard to be applied in some practical applications. It is mainly because these models are based on elements such as room thermal capacitances/resistance, airflow rate, heat transfer coefficient, heat gain coefficient, etc. These parameters are difficult to be measured precisely in old buildings. Also, as we mentioned above, the dynamic behavior of building room is very complex, it is nearly impossible to obtain an accurate mathematical model with limited number of parameters. The WSN, on the contrary, is highly transplantable as it could be quickly equipped in any buildings to gather real-time thermal data. Additionally, with ANN self-adaptive learning and mapping ability, it can capture the room's thermal response under different indoor/outdoor conditions. Based on the two reasons above, we believe that the combination of WSN and ANN can be an effective solution for indoor thermal modeling.

Previous studies outlined that ANN model outperformed Auto-Regressive(ARX) models in predicting the indoor temperature because the ANN models are more sensible to the nonlinearities of the thermal effects in buildings [10][11]. Furthermore, J.W.Moon has pointed out in his work [15] that ANN's adaptability makes it a more advantageous method in thermal control comparing to Fuzzy method. The thermal time constant (TTC) can be used to quantify the thermal inertia of a room, in simpler words, it describes how quickly the temperature changes under different thermal excitations. In previous works, the building TTC are calculated mostly with the thermal resistance and thermal capacitance of the building fabrics [16][17], these thermal constants is usually used to simulate the thermal response of buildings under environmental excitations, it is very difficult to use them directly to characterize the indoor temperature changes in response to existing indoor heating/cooling system. Some of the time constants are calculated based on simplifications that all heat transport phenomena in building are linear [17] which is limited facing the complex dynamic behavior of buildings. Thus, we proposed in this paper a new concept: the Effective Indoor Thermal Time Constant (EITTC). By

taking into consideration of both indoor heating/cooling system's performance and the building room's thermal property, the EITTC can be used directly to describe the indoor thermal response under existing indoor heating/cooling excitation and different outdoor conditions.

The proposed indoor thermal modeling solution is presented in Fig. 1. Accordingly, this work is carried out in four steps: firstly, we presented the concept of EITTC by establishing a mathematical model of a typical low energy efficient room. Secondly, a WSN based real-time thermal data acquisition system and an ANN integrated Graphic User Interface (GUI) software are built, followed by experiments on a confined prototype and a typical office building of 40 years old. The modeling performance on prototype and building rooms are consistent since the trained models' prediction errors regarding both training and test data are very low. Thirdly, by making linear approximations of these models, the variations of the model predicted EITTC have been discussed. Finally, based on the trained ANN thermal models, an indoor adaptive control system is developed.

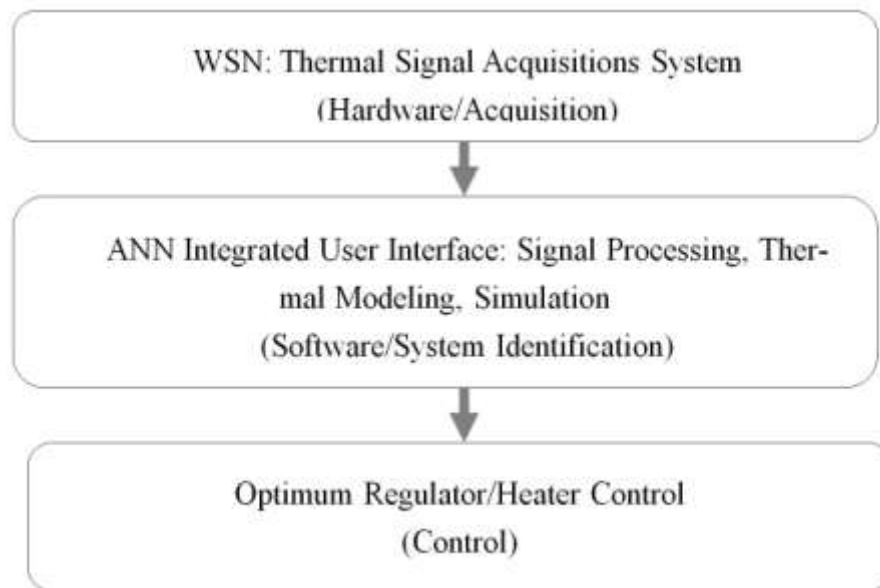


Figure 1 The principle schema

II. EFFECTIVE INDOOR THERMAL TIME CONSTANT

We take previous work [17] as a reference, the indoor thermal time constant proposed by J. Florez and G.C.Barney is:

$$\tau_r = \frac{C_r R_f R_o}{R_f + R_o} \quad (1)$$

Where τ_r is the room thermal time constant, C_r is the thermal flow store of the room, R_o is the linear thermal dissipater from the room to exteriors, and the linear thermal dissipater from room to the fabric is R_f . This equation is derived from a simplified linear mathematical model of a room; it is much a general expression of room thermal time constant.

We proposed in this paper the Effective Indoor Thermal Time Constant (EITTC) which is presented mathematically below:

We establish here a model of a typical building room (The room E106 in the Campus of Université de Toulon) as shown in Fig. 2.

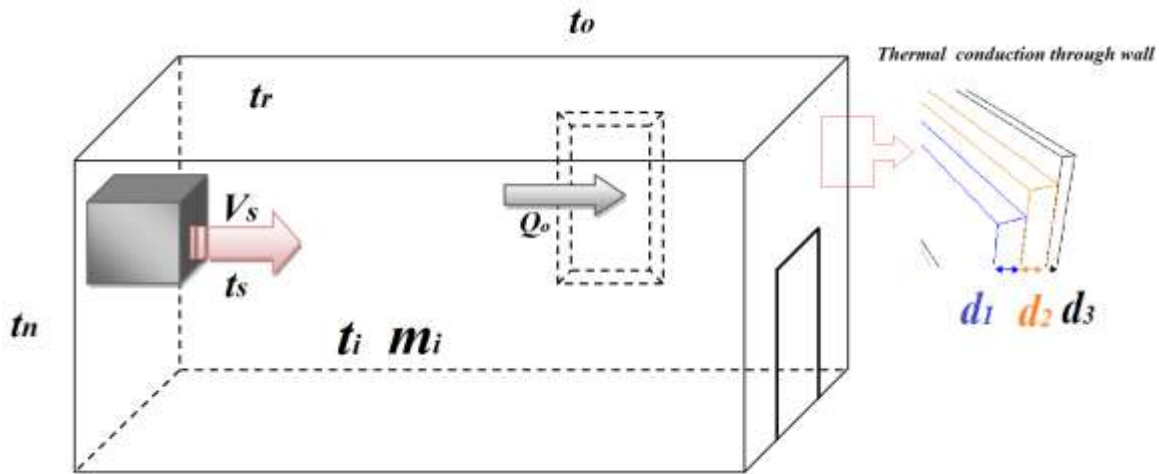


Figure 2. Model of a typical building room

If we define A_o , A_p , A_r , A_w as respectively the area of the wall towards exterior, the partition wall, the roof and the windows, accordingly, r_1 to r_4 are their thermal resistance. They can be calculated from the equation below:

$$r = \sum_{i=1}^n \frac{d_i}{k_i} + r_{in} + r_{ex} \quad (2)$$

In which, n is number of layers of the wall (see Fig. 2), d_i is the thickness of each layer and k_i is the thermal conductivity of each layer, r_{in} is the thermal resistance of air close to the interior surface while r_{ex} is the air thermal resistance close to the exterior surface.

We then have the absolute thermal resistance of different parts of the building room:

$$R_1 = \frac{r_1}{A_o}; R_2 = \frac{r_2}{A_p}; R_3 = \frac{r_3}{A_r}; R_4 = \frac{r_4}{A_w} \quad (3)$$

Thus, the thermal conduction on each part of the room is:

$$\Delta Q = \Delta Q_d - \Delta Q_o + \frac{\Delta t_o}{R_1} + \frac{\Delta t_n}{R_2} + \frac{\Delta t_r}{R_3} + \frac{\Delta t_o}{R_4} \quad (4)$$

where t_i , t_n , t_r , t_o are respectively the indoor temperature, the next door's temperature, the temperature of upper room and outdoor temperature; According to the energy-conservation law, this room model can be put as:

$$m_i c_r \frac{dt_i}{dt} = \rho_s V_s c_s (t_s - t_i) + \frac{t_o - t_i}{R_1} + \frac{t_n - t_i}{R_2} + \frac{t_r - t_i}{R_3} + \frac{t_o - t_i}{R_4} + Q_i - Q_o; \quad (5)$$

where m_i is the thermal mass of indoor air and c_r is the indoor specific heat capacity; t_s is the output heated air temperature from the indoor heating system, ρ_s is the density of heated output air, V_s is the volume of heated output air and the temperature of heated air is defined as t_s ; c_s is the specific heat capacity of heated output air; Q_i is the sum of heat (kW) emitted by the indoor activities and Q_o is the heat lose through the opened windows or doors.

The incremental equation derived from Eq. 5 can be expressed as following:

$$\tau \frac{d\Delta t_i}{dt} + \Delta t_i = G_1 \Delta V_s + G_2 \Delta Q; \quad (6)$$

In Eq. 6, we have:

$$G_2 = \frac{1}{\rho_s c_s V_s + \frac{1}{R_1} + \frac{1}{R_2} + \frac{1}{R_3} + \frac{1}{R_4}}, \quad (7)$$

$$\tau = \frac{m_i c_r}{\rho_s c_s V_s + \frac{1}{R_1} + \frac{1}{R_2} + \frac{1}{R_3} + \frac{1}{R_4}} = m_i c_r G_2 \quad (8)$$

$$G_1 = \frac{\rho_s c_s (t_s - t_n)}{\rho_s c_s V_s + \frac{1}{R_1} + \frac{1}{R_2} + \frac{1}{R_3} + \frac{1}{R_4}} = \rho_s c_s (t_s - t_i) G_2 \quad (9)$$

$$\Delta Q = \Delta Q_d - \Delta Q_o + \frac{\Delta t_o}{R_1} + \frac{\Delta t_n}{R_2} + \frac{\Delta t_r}{R_3} + \frac{\Delta t_o}{R_4} \quad (10)$$

Where τ is the Effective Indoor Thermal Time Constant, G_i is the amplification factor of the indoor temperature caused by heated air; G_2 is the amplification factor of indoor thermal perturbation; ΔQ is the total change of the indoor heat caused by all disturbances.

The EITTC, as shown in Eq. 8, describes how quickly the indoor temperature changes under different indoor heating stimulation and outdoor conditions. It indicates that EITTC is mainly related to three factors: the indoor heat capacity, the indoor heating/cooling system's efficiency and the thermal conductivity. As we mentioned in the introduction, nonlinear and time-varying thermal effects have long been recognized in buildings. The parametrical modeling method need precisely measured parameters which are hard to obtain in these old buildings. Furthermore, it is not very practical for habitants to use this method to characterizing the thermal response in their rooms. In this paper, we propose to estimate the room's EITTC by establishing an adaptive ANN indoor thermal model based on WSN acquisitions. The realization of the proposed method is presented in the following parts of this paper.

III. WSN BASED HARDWARE AND ANN SOFTWARE DESIGN

To make this work more applicable, we developed a set of industrial level hardware and software solutions including a WSN based thermal acquisition system, an ANN integrated Graphic User Interface (GUI) software and an infrared heating source (air-conditioner) remote control circuits.

The WSN system is cored with Texas Instrument (TI) CC2530 microcontroller and embedded with ZigBee 2007 specification (ZigBee defines a reliable, cost effective, low rate, low-power wireless networking. It has many advantages in forming a network with long operating time and a huge quantity of sensor accesses. As we need long term acquisitions with sensors covering the whole building rooms, it is therefore considered as an appropriate choice for us). The WSN system mainly contains three types of devices: Coordinator, Router, and End-device. Digital temperature sensor, solar radiation infrared sensor are integrated on the End-device.

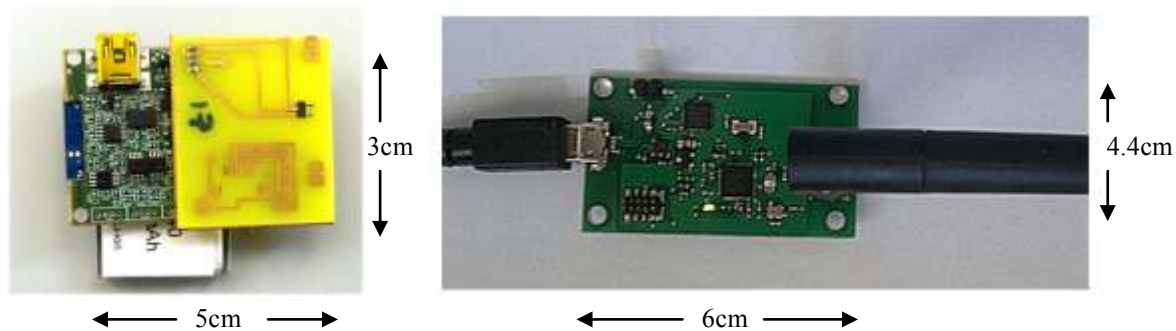


Figure 3. End-device and Coordinator of the WSN system

Table 1: Parameters and features of the WSN system.

Feature of the WSN system	Values
Cost per unit	10 euros
Network Coverage	20m/100m
Consumption in operational mode	42mA
Consumption in Power saving mode	125 μ A
Battery Life	>200h
Reliability	High
Packet loss ratio	<0.03
Installation	Easy
Network capacity(Nodes per Network)	240/25920

Accordingly, we developed the ANN integrated GUI software under Visual Studio (see Fig. 4). The main functions of this software are 1. Data storage: where measured sensor data can be stored in the database. 2. Signal processing: different digital filters have been integrated in this software to process the coming-in sensor data. 3. ANN integrated thermal modeling. 4.

Simulation, Model-prediction and control. 5. Real-time observation of sensor acquisition and 2D simulation.

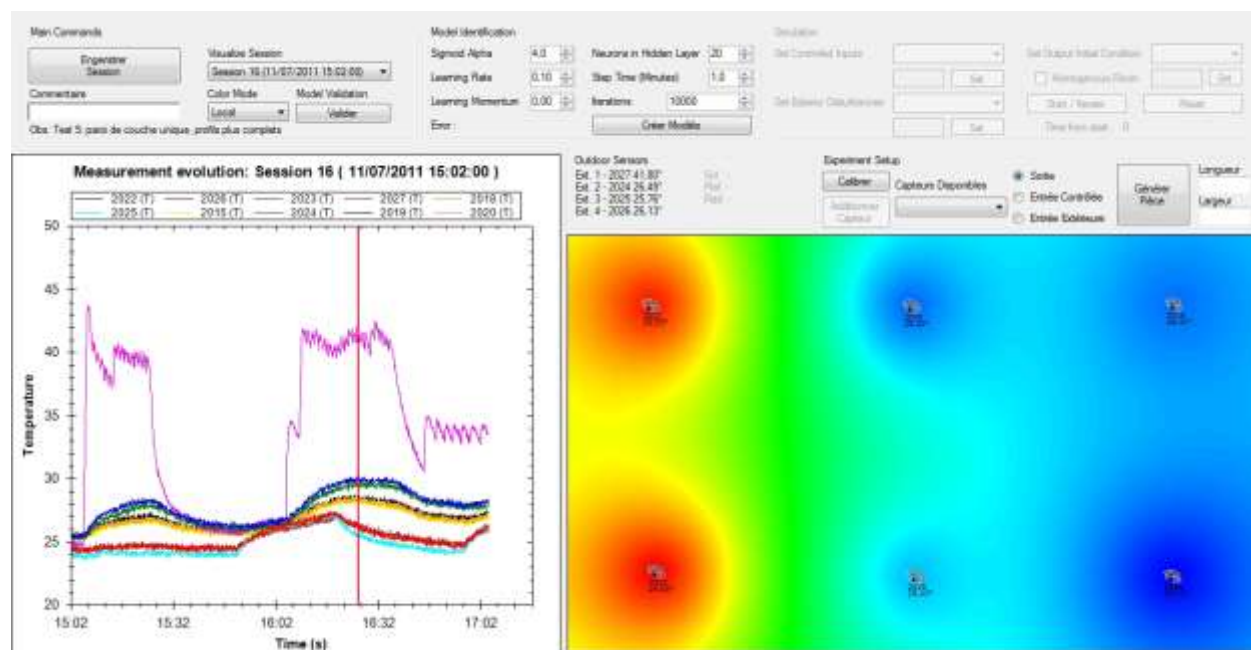


Figure 4. ANN integrated thermal modeling software

The thermal model established in this work is a typical Multi-Inputs Multi-Outputs (MIMO) system: we consider the indoor heating or cooling source as a main control input, the measured outdoor temperature and solar radiations as perturbation inputs. The temperatures on each point of the building room are henceforth defined as the outputs. To fit this MIMO system, a three-layered Back-Propagation Neural Network (BPNN) is chosen as the ANN model structure. The BPNN proposed by Rumelhart *et al* [18] is one of the most commonly used neural networks for its simplicity and efficiency. Hecht-Nielsen demonstrated that a three-layered BPNN is capable of approximating any continuous mapping [19]. Previous research has also confirmed its performance in engineering applications [20]. Correspondent to the MIMO system, the BPNN contains three layers: an input layer, a hidden layer and an output layer. This determines a first order BPNN structure. In order to increase the model's accuracy, we also proposed higher order models: if we define the standard interval time between every acquisition as T_i , we can form a second order model by involving the previous output temperature $t-T_i$ in the input layer (see Fig. 5), or even a third order model by including both $t-T_i$ and $t-2T_i$ in the input layer, etc.

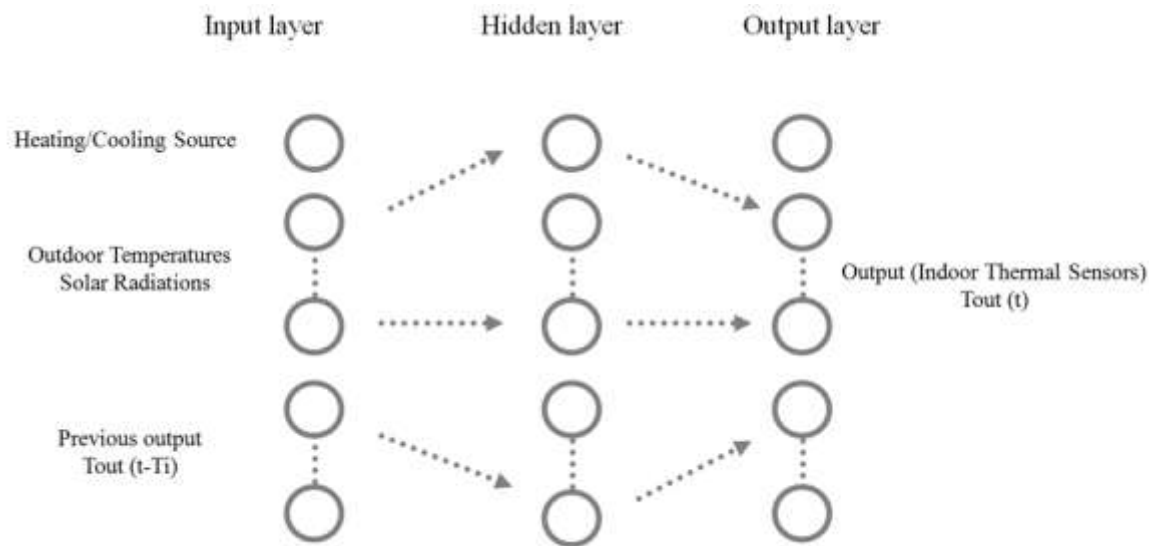


Figure 5. Second order ANN thermal model structure

The inputs of the model affect the outputs with different weights. During the training phase, the neurons will regularly correct their weights by calculating the error between current ANN model’s output and the expected output. After sufficient learning iterations, the error can be considered negligible. At this point, we consider the model is ready and well taught. In this work, we build our network model with a default training iterations of 500000 times and the default error threshold is set to 0.00003. These can be found in the configuration of training parameters in Fig. 6.

Figure 6. Configuration of ANN Training parameters

This algorithm of training is presented below. As the mathematical representation of the complete model is very complicated, we take a simplified one neuron model (see Fig. 7) as an example to explain the model’s training algorithm. If we consider that the two main inputs are Indoor heating/cooling control sources C_s , the ambient temperature T_a , the only output is the indoor

temperature T_{out} . Then, the activation function of the neuron is $f(x)$ and it is responsible for normalizing the incoming values from the previous layer.

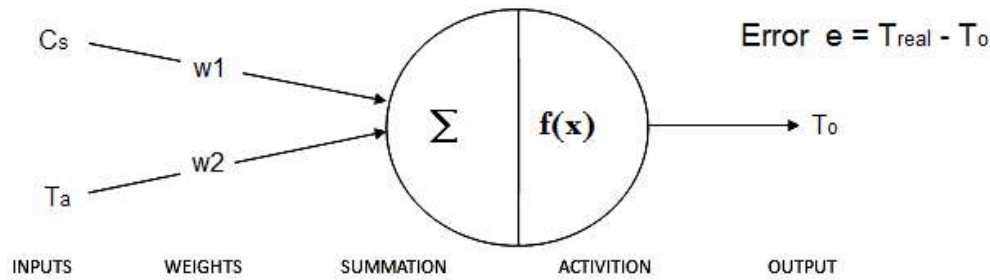


Figure 7. Example of a single neuron

A sigmoid function (11) is chosen as activation function $f(x)$ in the software. A three-layered BPNN using sigmoid activation function is a universal approximator [21].

$$f(x) = \frac{1}{1 + e^{-x}} \quad (11)$$

If we define:

$$u = c_s w_1 + t_a w_2 \quad (12)$$

then, we have the output of the single neuron equals to:

$$T_{out} = f(c_s w_1 + t_a w_2) = f(u) \quad (13)$$

After the inputs have reached the output layer through all the neurons in the network, these outputs will be compared with the measured output values. The difference is defined as the error signal e of the output layer neurons in Fig. 7. The error signal propagates backwards to the input layers. After the error signal e of every neuron in the model is computed, the weight of each neuron adjusts itself through an optimization gradient descent method, where η is the learning rate. In this way, the error decreases:

$$w_1' = w_1 + \eta e \frac{df(u)}{du} C_s \quad (14)$$

$$w_2' = w_2 + \eta e \frac{df(u)}{du} T_a \quad (15)$$

So far, there is no determined rule to define the best network training parameters, the reasonable method is still trial and error. Thus, we give two possibilities in this software: 1. Manual Definition, the parameters can be defined by users; their default values are presented on the

software in Fig. 6. 2. Auto Evaluation, the parameters can be selected by a cyclic trial algorithm: different sets of training parameters are used to train network models. The software will select the parameter combination which leads to the minimum prediction errors regarding the training sets. The training method can also be found in author's published work on WSN based ANN modeling [13].

As for the number of neurons in the hidden layers, we estimated it with equation below:

$$\text{Num. of Hidden Neurons} = \frac{1}{2}(N_i + N_o) + \sqrt{N_{tp}} \quad (16)$$

Where N_i is the total number of network inputs, N_o is the number of outputs, N_{tp} is the number of training data patterns. This formula has been used in several engineering problems for modeling and prediction with good results [22].

One contribution we introduced in this work is “Step-Time” which defines a time interval to sequence the sensor data to form the training data matrix (see Fig. 8). Since the frequency of WSN acquisition is high, a single session of acquisitions contains a huge amount of sensor raw data in the software database. In order to train ANN model more efficiently, instead of taking all the sensor data from database, the training data matrix for the ANN model is selected sequentially from the raw sensor data according to the Step-Time.

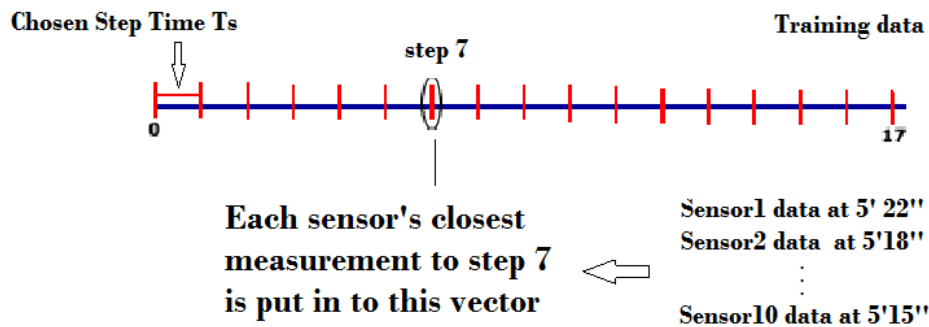


Figure 8. The Step-Time and training data set

IV. EXPERIMENTS: PHOTOTYPE AND ROOM

Experiments were divided into two phases: First, to evaluate ANN the modeling performance with WSN, experiments have been done on a prototype. After its performance on prototype was verified, we carried out experiments in real building rooms. The prototype is a cubical corrugated box. To simulate a room inside a building, we have covered our prototype with same boxes above and four around, leaving only one side towards thermal source. The prototype is placed in a room where the indoor temperature is considered stationary and no circulating air flow presented during experiments. It simulates several separated thermal resistance zones just like a building. Admittedly, the thermal characteristic of cubical corrugated box differs from the construction materials. Although the heat transfer coefficient (also known as the U-value¹) of the cubical corrugated box (board thickness 4.23mm) is $2.21 W/Km^2$ while the U-value of the building wall (Aggregate Concrete, wall thickness 0.3m), according to our calculation, is about $5.83 W/Km^2$. they share the same heat transfer principle. The experiment is described below: Three sensors (in blue in Fig. 9) are located outside the prototype as disturbances (input), measuring ambient temperatures. One sensor (in red in Fig. 9) measuring the thermal source is considered as control input. Six thermal sensors (in pink in Fig. 9) are put horizontally inside the prototype to collect inner temperatures, giving the output value of the system (see Fig. 9).

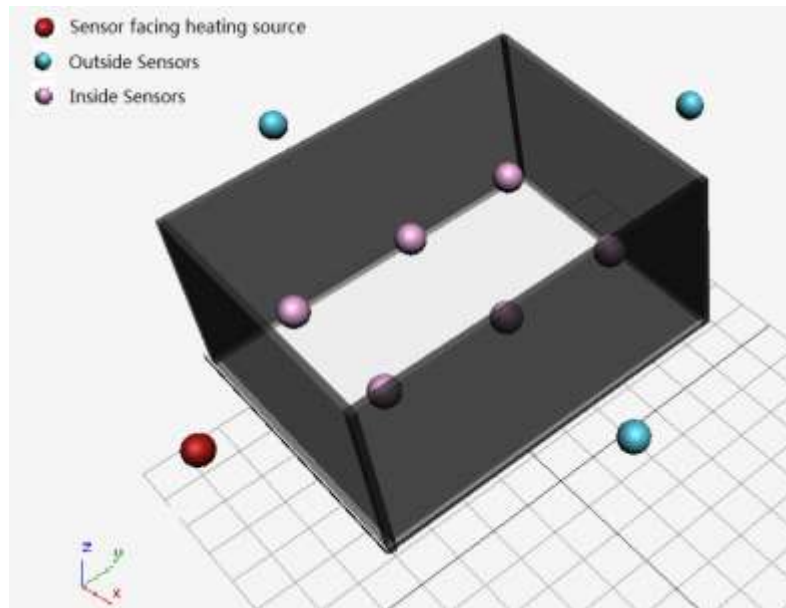


Figure 9. Over all view of the prototype

¹ The U value is an energy efficiency indicator. It refers to the thermal transmittance.

Later, experiments have then been carried out in real building rooms E106 (Width 5.5m, length 7.2m, Height 3.15m) located in the building E of IUT in the campus of University of the South, Toulon Var (LAT 43° 123' N, LONG 6° 11' E), city of La Garde, south France. The building was built in the year of 1968 and has not yet been renovated. It matches the definition of low energy efficient buildings: no modern HAVC system inside and it is badly isolated. One infrared sensor is installed outside the building room to measure solar radiations. One thermal sensor is placed outside the building while the others are placed in the corridor. These two sensors collect the ambient temperatures outside the room. The indoor heating/cooling source is considered as the main input. Six thermal sensors are placed horizontally at the height of 1.10m². The experiments are mainly carried out in this room (See Fig. 10). The ANN models are automatically trained by sensor data and stored in the database.

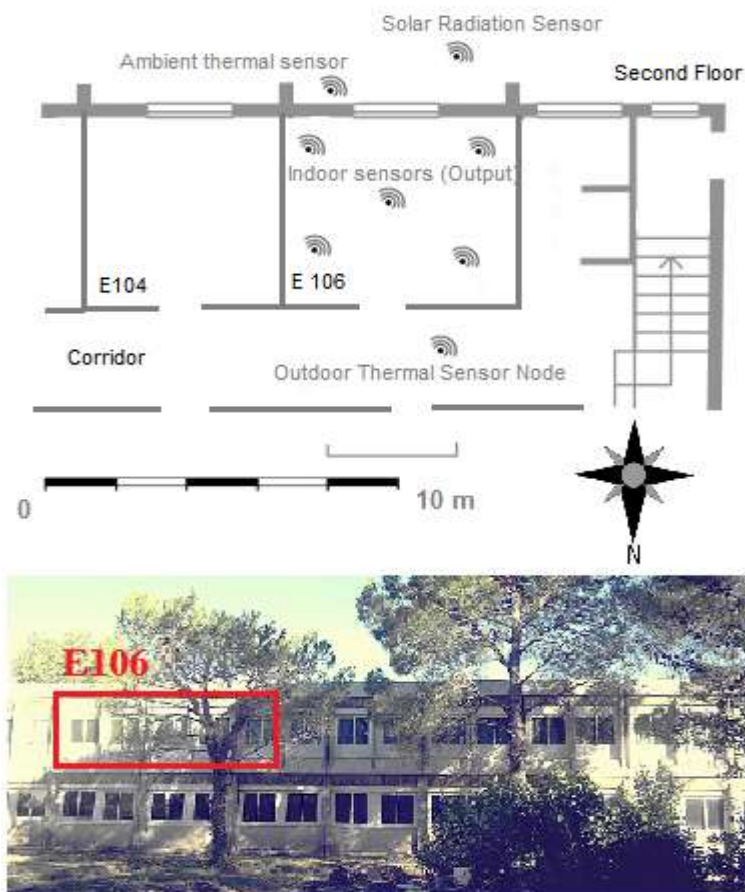


Figure 10. Room E106 in Université de Toulon, Var, France

² According to air-conditioning industry standard, the room temperature is evaluated at the height of 1.10m where the most human activities take place.

V. INDOOR THERMAL MODEL BASED ADAPTIVE CONTROL

As the most energy consuming period for building room E106 located at this latitude is the early spring, the indoor heating system is operated manually for all day long, which generate great energy wastes.

Thus, we designed in this work a new indoor heating control strategy called “Adaptive Start/Shut Control” which is based on the ANN thermal model’s prediction. The necessity of adaptive Start/Shut control can be understood with Fig. 11. The accurate Start/Shut control of indoor heating equipment can lead to the both indoor comfort and a minimum energy consumptions. By deploying the WSN based ANN thermal model, precise predictions and control of indoor temperature can be achieved: Firstly, the computer records the actual initial outdoor/indoor conditions from real measured WSN sensor acquisitions. Secondly, the software uses the correspondent trained ANN thermal model to make the calculation of the preheat time (t_p) needed. Thirdly, calculation will be made to find the optimum start time of indoor heating equipment based on the occupancy start time and the model prediction ($t_{in} - t_p$). Finally, the software generates control command and sends it to activate the heating system. The same process can be applied for an earlier shut-off of the heating system (see Fig. 12). This control operation can be used to shorten the heating period and bring direct energy saving.

This control method has been proved effective by experiments carried out during the spring 2013 and 2014 in the room E106. Normally, the heating system in this room is activated from 8:00 am to 6:00 pm while the occupancy period is from 8:45 am (t_{in}) to 5:45 pm (t_{out}). By deploying the proposed control method, the adaptive start and shut off of heating system is controlled precisely based on model’s predictions. Thus, the operating period of the heating system is shortened. The results are presented in the next section of this paper.

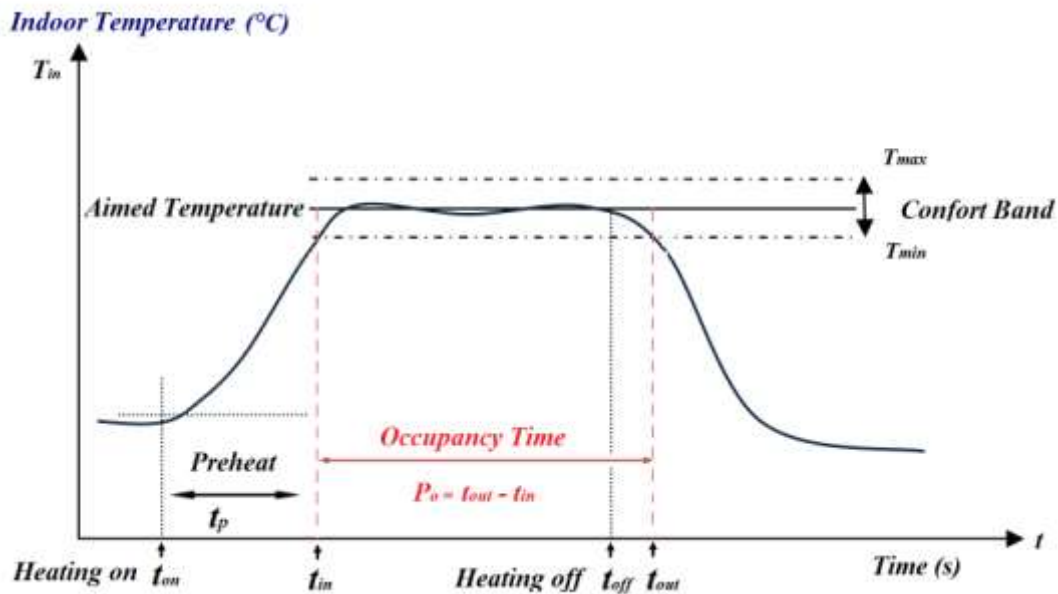


Figure 11. Optimum indoor heating operation

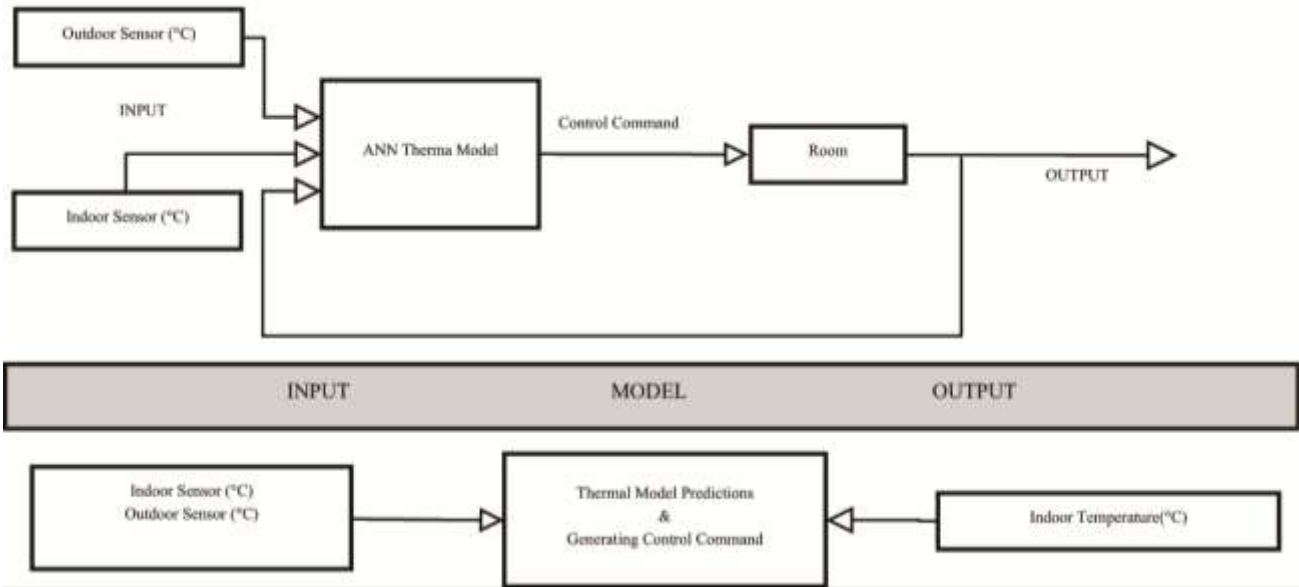


Figure 12. Indoor thermal model based predictive control

VI. MODELING AND CONTROL: RESULTS AND DISCUSSION

In order to evaluate the modeling results, an Average Mean Squared Error (AMSE) of the ANN model are presented in Tab. 2. This value is calculated as below (see Eq. (7)-(8)). If we consider the model predictions output is T' and the measured temperature is T , the number of measures is n ; we have the Mean Squared Error (MSE) for one model output (one sensor) is:

$$MSE = \frac{1}{n} \sum_{i=2}^{n+1} (T'(i) - T(i))^2 \quad (17)$$

The AMSE is the average MSE value of all the k outputs (k sensors):

$$AMSE = \frac{1}{k} \sum_{i=1}^k MSE(k) \quad (18)$$

The modeling results on prototype are presented in Fig. 12. We compare the model response regarding its test data in Fig. 12. The originally measured outputs (multiple sensors) are colored, the model responses are in black. The results of real indoor thermal modeling results is presented in Fig. 13, the model predictions are in black while measured data are lightly colored.

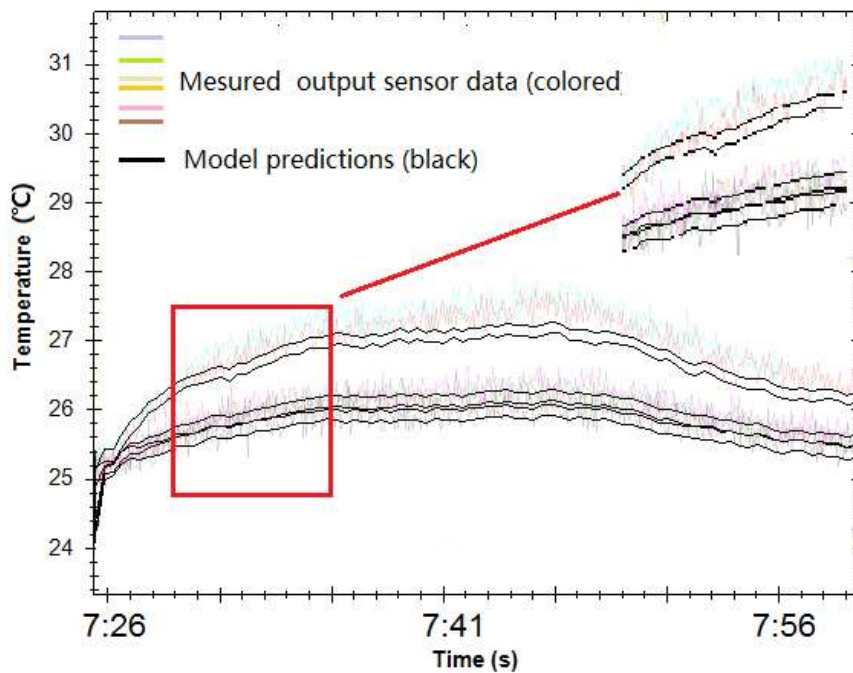


Figure 13. Prototype: ANN model response (black) regarding measured test data (colored)

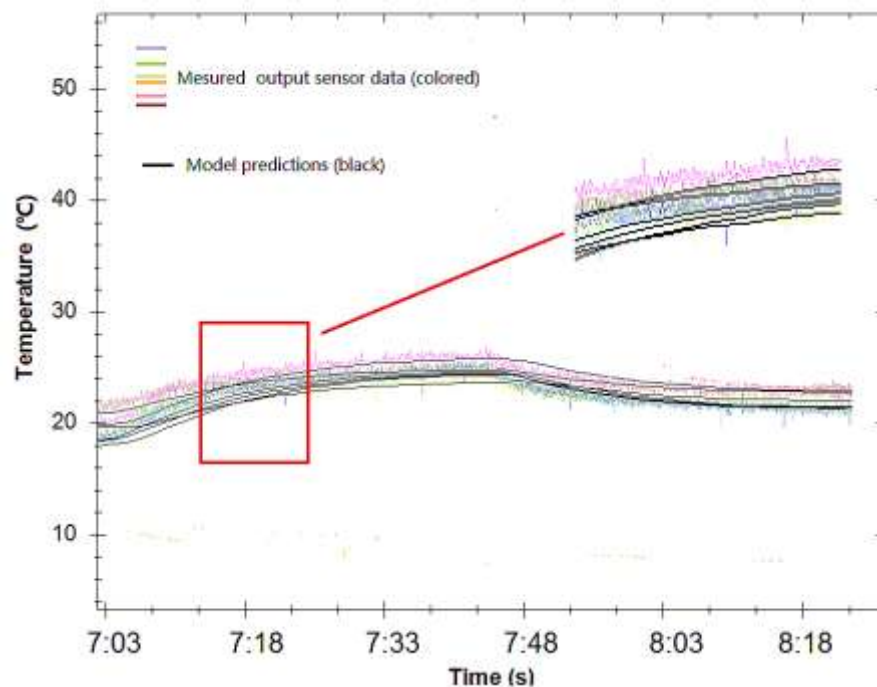


Figure 14. Indoor: ANN model response (black) regarding measured test data (colored)

In order to verify all models' performance, we calculated the AMSE of all the 93 models created individually from 93 different sessions of daily acquisitions, the average prediction errors regarding its own training session is around 0.20 °C while regarding the test data is about 0.27 °C.

Table 2: AMSE of ANN thermal model based on real building experiments

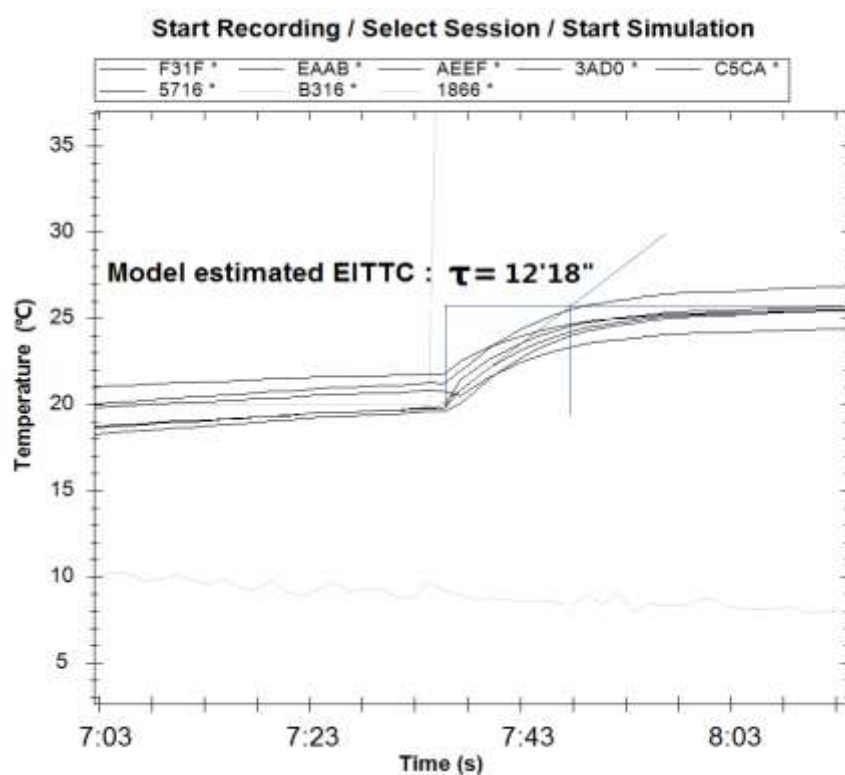
Performance Criteria	AMSE
Against Training data	0.20 °C
Against Test data	0.27 °C

The modeling results have positively indicated the fact: based on the WSN thermal sensor data, ANN's self-adaptive learning and mapping ability makes it possible of providing accurate framework for indoor thermal modeling of a building room. The raw thermal data and model predictions match the previous research on zonal model of buildings [23-27]. It shows that the temperature distribution inside the building room is not homogeneous. Different parts of room

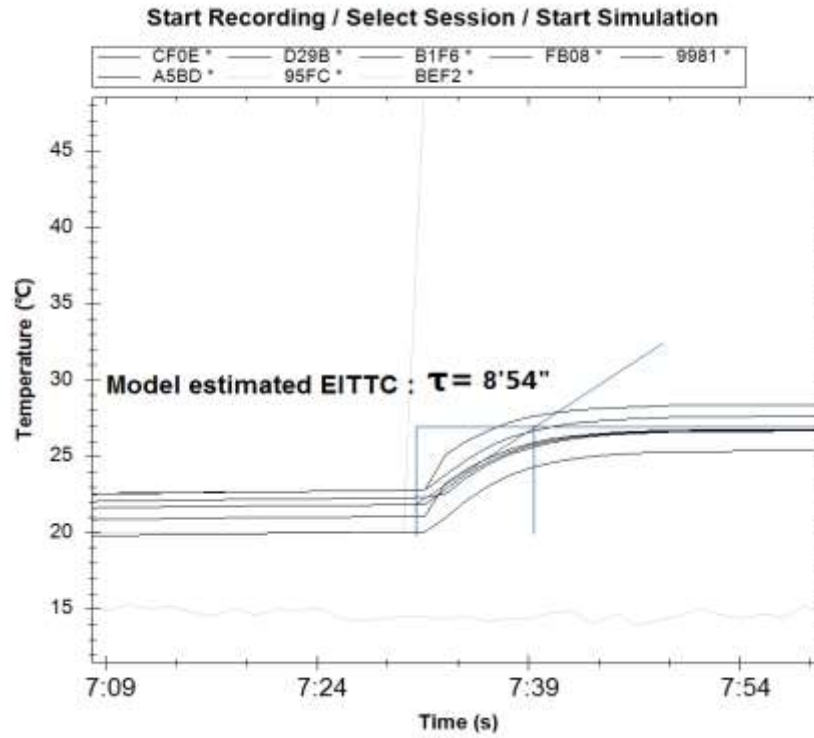
react differently to the heating source, which is mainly due to the thermal dynamics and air flow mechanics. This result indicates that the WSN and ANN are capable of capturing the thermal characteristics on each part of the room.

In order to characterize the general thermal response in the room, linear model derived from the previously established ANN thermal model is considered valuable. By simulating the step response of the trained ANN thermal models, the first order approximation on each part of the room can be realized. Based on these simulations, the average EITTC can then be evaluated.

Two examples of the ANN thermal model's step responses are presented in Fig. 15. We find that the models' predictions on EITTC vary under different indoor/outdoor conditions. To verify these ANN model's predictions on indoor thermal time constant, we compared the ANN models' predicted time constants with real measured indoor temperature's characteristic time. This comparison shows the consistency between model's prediction and the real indoor thermal response. The results are presented below in Tab. 4. Statistic computation has been made. The correlation rate between the model predicted EITTC and the measured room thermal characteristic time is about 0.9526 (with a p-value $p < 0.041$).



a. Step response of ANN model created Feb. 23, 2012



b. Step response of ANN model created *April. 06, 2012*

Figure 15. Model predicted EITTC on different dates

Table 3: Model predicted EITTC and measured room characteristic time (minute)

Date	EITTC	Measured CT	Date	EITTC	Measured CT
23/2/2012	12.3	12.9	13/10/2012	8.6	9
21/2/2012	12.2	12.7	17/10/2012	8.9	9.5
2/3/2012	12.7	11.5	25/10/2012	9	10
6/3/2012	13.1	14	28/10/2012	12.5	13.4
9/3/2012	12.1	14	30/10/2012	11.2	12
14/3/2012	10.9	11.2	3/11/2012	10.8	11.5
19/3/2012	10.6	11.4	9/11/2012	11	11.8
23/3/2012	9.1	10.9	12/11/2012	12.5	13.4
27/3/2012	8.7	9.6	16/11/2012	12.8	13.6
30/3/2012	8.9	9.8	20/11/2012	10.8	11.8
2/4/2012	8.8	9.5	26/11/2012	8.9	10
6/4/2012	8.9	9.9	28/11/2012	11.2	12.2
9/4/2012	8.5	9.7	30/11/2012	12.9	13.8
10/4/2012	9	10.4	5/12/2012	13.2	14.1
11/4/2012	8.9	10.5	14/12/2012	13.4	14.5
12/4/2012	9	10.7	20/12/2012	13	14

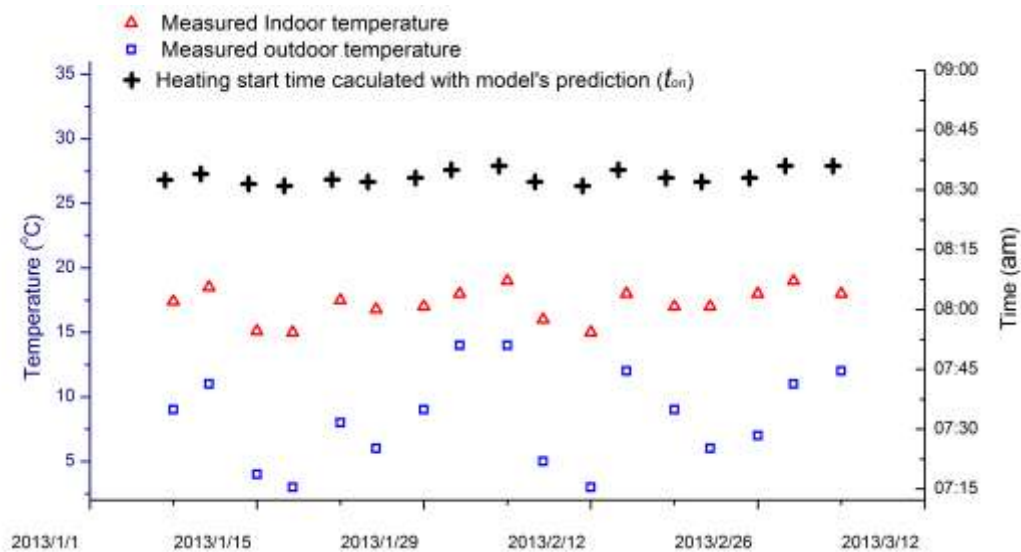
In Tab. 3, Measured CT refers to the measured room Characteristic Time. We noticed that the predicted time constants are a little bit shorter (average error is $0.85min$ with a standard deviation of 0.1978) than the measured room characteristic time. The main reason is that the model estimated EITTC are simulated from the step response of the ANN model. In reality, indoor temperature changes resulting from heating system always presents certain delay.

The models' predictions show that the EITTC of this building room varies from 8.5 minutes to 13.4 minutes. This result can be discussed from different perspectives. Firstly, we noticed that time constant changes in response of different environmental factors, for example, the outdoor temperature. This fact well demonstrated the fact that nonlinear heat transfer phenomena presents in buildings. As we can see from Eq. 8 that except for the non-linear thermal conductivity, that the EITTC is also related to the indoor heating/cooling system's output. Most heating/cooling source like inverter air-conditioning system has nonlinear output; this can be considered as the second cause of the variable EITTC.

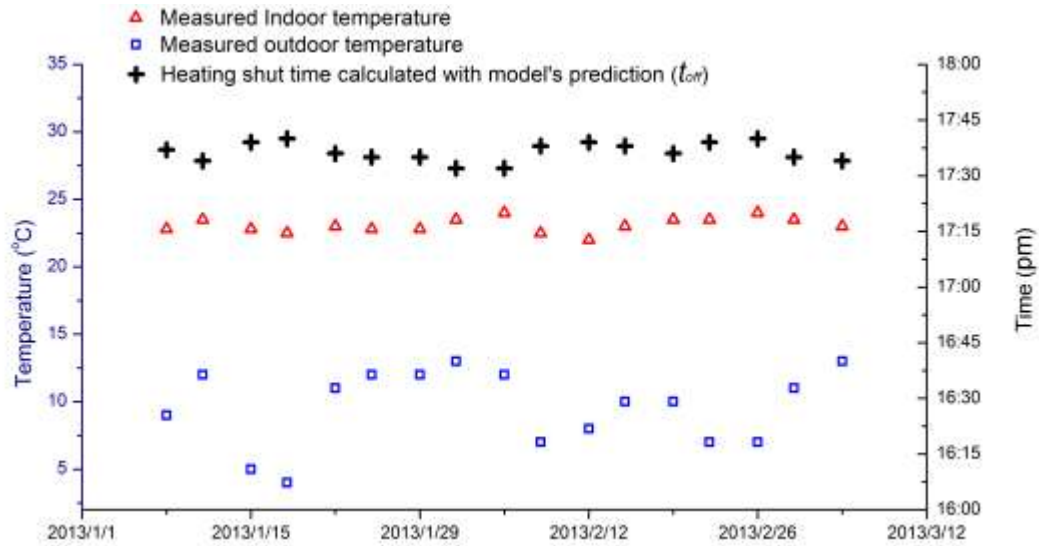
For building habitants, it is difficult to obtain the exact mechanism of their indoor air-conditioning system to make a quantitative analysis. This in return points out again the advantage

of our WSN and ANN combined solution: benefiting from the universal approximating ability of ANN models, habitants can characterize their indoor thermal effects without further computation or parameter estimation on their existing heating/cooling system. Based on the discussions above, the ANN thermal model is able to describe building room's thermal response adaptively. Furthermore, it could characterize the existing control source's heating effects in the building room under different indoor/outdoor conditions. WSN is practical to be implemented in the whole building permanently to trace the thermal characteristics under different conditions and to give in-time predictions. For example, predictions could be made based on the weather reports. Thus, dynamic control could be realized according to these predictions.

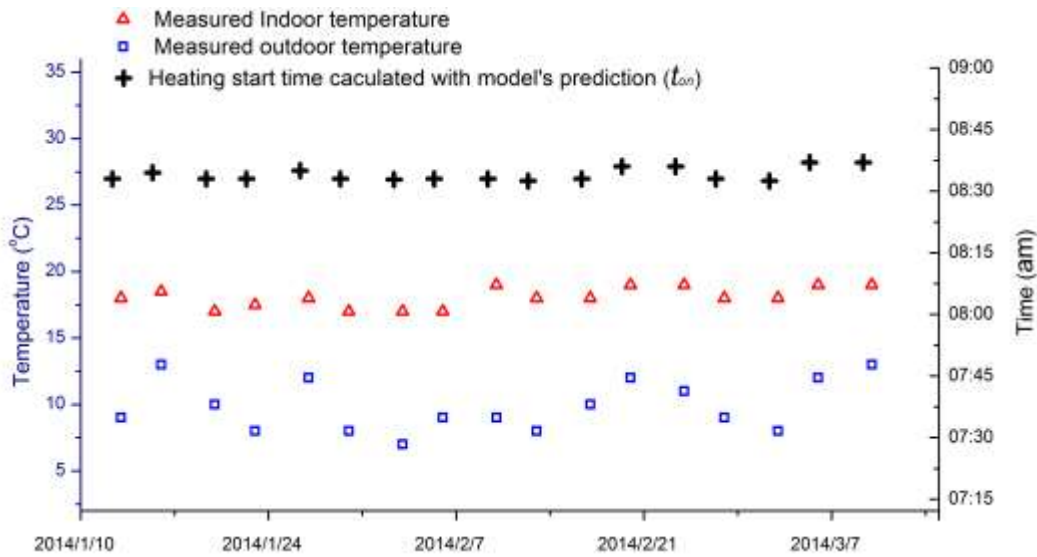
As introduced in the previous section of this paper, we proposed model based adaptive heating start/shut control in the room E106 to shorten the operating period of the indoor heating system. By deploying the adaptive Start/Shut control system in room E106, further energy efficiency has been achieved. The heating start/shut tests (spring 2013 and 2014) are presented in Fig. 16. Comparing to the old Start/Shut operation of heating system (08:00 am to 6:00 pm), the new control method has shortened 9.3% of the regular heating period which leads to direct energy saving.



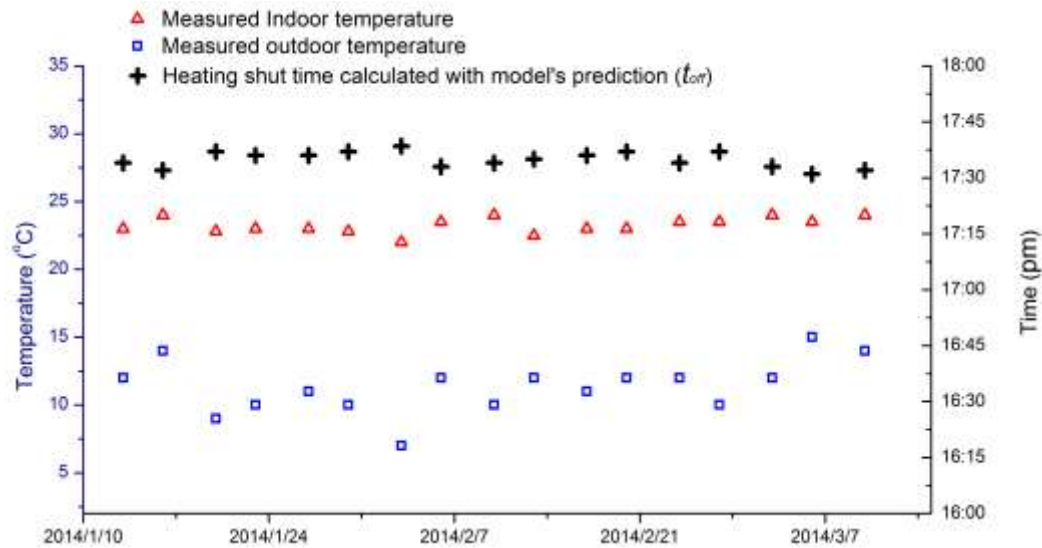
a. Model based heating start control test spring 2013



b. Model based heating shut control test spring 2013



c. Model based heating start control test spring 2014



d. Model based heating shut control test spring 2014

Figure 16. Adaptive heating start/shut control results

VII. CONCLUSION

This paper has highlighted a new indoor thermal modeling solution to characterize the thermal response in low energy efficient buildings. We proposed a new concept EITTC (Indoor Efficient Thermal Time Constant). It shows that the combination of WSN (real-time acquisition) and ANN (system identification tool) leads to adaptive fine grained indoor thermal model. Experiments on both prototype and faculty building room positively exhibited consistent results. By tracing the characteristics time constant of the linear approximation of the ANN thermal model, we can characterize the existing control source's heating/cooling effects under different outdoor conditions. These results have been confirmed by statistical computations since a strong correlation have been found between the model predicted room time constant and real measured characteristic time of the building room. Adaptive heating control methods have been proposed and showed direct effects in building energy savings. Further research and explorations will be made: taking advantage of the high energy efficiency of our WSN system, long term measurements for the purpose of enriching the thermal models will be necessary.

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